Journal of the Eastern Asia Society for Transportation Studies, Vol. 6, pp. 2702 - 2717, 2005

DYNAMIC ORIGIN-DESTINATION FLOWS ESTIMATION FOR FREEWAY CORRIDORS USING GENETIC ALGORITHM

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Abstract: Real-time origin-destination (O-D) flows are important input data for most freeway management systems, and very difficult to obtain. This research puts forward two categories of parameter optimization models for estimating dynamic O-D flows in freeway corridors. The proposed models make full use of information from ramp traffic counts and mainline flow measurements, which are provided by surveillance systems. The models also take into account time-varying route travel time, which is estimated by using a recursive method reported in this paper, and realistically formulate the nonlinear dynamic interrelations between O-D fractions and traffic flow measurements. A genetic algorithm is presented to improve the accuracy and operational efficiency necessary for practical applications. The results of simulation experiments indicate that the proposed methods are rather accurate, robust and efficient, and offer the potential for real-time applications.

Key Words: dynamic origin-destination flows, time-series of traffic counts, genetic algorithm

1. INTRODUCTION

Real-time origin-destination flows between entry and exit of freeway corridors are most important input data for ramp metering system, traveler information system and quick response system for urgent incidents, etc. However, getting dynamic O-D flows directly from conducting surveys is very difficult and costly. At the same time, deployment of ITS, especially ATMS, is providing researchers and practitioners with an unprecedented amount of valuable on-line and off-line traffic data. These data can be used in different applications such as traffic simulation, traffic control and ATIS. Nevertheless, ITS data have been used primarily to support real-time operational applications, while other potential uses of these data have been largely ignored up until now. In this paper, the effort to extract knowledge, especially time-series of traffic counts, from the on-line or off-line data gathered by ITS is focused on the estimation of dynamic O-D flows using optimization methods.

Over the past two decades, the development of an accurate and efficient method for dynamic O-D flows estimation from link traffic counts has received increasing attention among transportation researchers. Conventionally, O-D flows are considered only for a certain time period of interest, and thus are estimated with the average traffic counts of that period. Commonly, these methods can be classified into four categories: generalized least-squares, maximum likelihood, entropy maximization and Bayesian inference methods. A comprehensive review of research along this direction can be found in Cascetta and Nguyen (1988). Further more, Yang, H. *et al.* (1994) and Yang (1995) also put forward some equilibrium-based and bi-level estimation methods. Such methods are static in nature, and can not be directly used in real-time systems.

With respect to the research on dynamic O-D estimation, Cremer and Keller (1981), Cremer and Keller (1984) and Cremer (1983), in a series of pioneering work for identifying intersection flow movements, have first employed relations constructed through time-series of traffic counts, and converted the underdetermined static model to an overdetermined dynamic formulation. Nihan and Davis (1987), Cremer and Keller (1987) and Jiao, P.P. *et al.* (2003) have also respectively presented a set of dynamic O-D estimation models for intersections or small networks based on the prediction-error minimization methods. A rather general review of studies in this category is available in Bell (1991).

Note that to estimate O-D flows with either static or dynamic methods, the relations between O-D matrices and traffic counts, in other words, system equations, must be given or partly known. In static case, since the relations between O-D pairs and link flows are relatively well established through static traffic assignment models, most of those methods are applicable in general networks. In contrast, most methods developed for dynamic O-D estimation are limited to small networks such as individual intersections or small freeway corridors, because of the difficulty in establishing the dynamic relations between time-varying O-D and link flows. Though dynamic traffic assignment methods have been studied extensively in recent years, such as Peeta (1994), Ran and Boyce (1994), Chen (1999) and Mahmassani, H.S. *et al.* (1998), they are still rather far from practical use, especially for a congested network.

Another category of studies for estimating the complex dynamic O-D matrices focuses on formulating the model based on state space. Okutani (1987) formulated a Kalman filtering model for dynamic O-D estimation and prediction, using an autoregressive model to capture the temporal interdependency among O-D flows and link counts. Along the same line, Ashok and Ben-Akiva (1993, 2000, 2002) have revised Okutani's work with the state variables representing the deviations of O-D flows from prior estimates based on corresponding historical data. However, all these methods are based on the assumption that an accurate dynamic traffic assignment model exists, and prior available time-dependent O-D data are available. Unfortunately, the development of a reliable dynamic traffic assignment model and the acquisition of historical dynamic O-D data are both quite challenging tasks, and may not be solved in the near future.

Fortunately, there exist unique properties in freeway corridors that provide valuable information for their dynamic O-D estimation, and the dynamic relations between O-D pairs and link counts can thus be formulated. Chang and Wu (1994) proposed a recursive model along this line, and applied extended Kalman filtering to solve it. Though Kalman filtering is rather efficient, its results is not very satisfying, and the traffic delay is not taken into account in the estimation of time-varying travel time, which might be rather big in a congested freeway. In this paper, a further research for freeway corridors will be conducted, an integrated estimation method of dynamic travel time will be proposed, and a more exact genetic algorithm will be applied to solve the problem.

This paper consists of the following sections. The variable definitions and a nonlinear dynamic relation between time-dependent O-D flows and time-series of traffic counts in freeway corridors are illustrated in Section 2. Since travel time in freeway corridors can not be neglected, a recursive approach for estimating time-varying travel times are introduced in Section 3, which takes traffic delay into account. Further more, two revised parameter optimization models with the objective functions to minimize the sum of absolute differences between observed and estimated traffic counts are represented in Section 4. Based on the characteristics of this model, a genetic algorithm and its key issues are addressed in Section 5. The evaluation results based on simulation experiments are reported in Section 6. Conclusions and further research are summarized in the last section.

2. VARIABLE DEFINITION AND PROBLEM FORMULATION

Consider freeway corridors as shown in Figure 1.

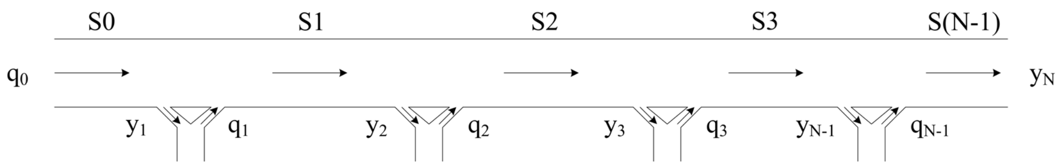

Figure 1. Sketch Map of a Freeway Corridor

The above freeway corridor is composed of N sub-corridors and (N+1) nodes. Sub-corridors are denoted as S0, S1,……, S(N-1). Except for S0 and S(N-1), each sub-corridor has a pair of ramps, in other words, on-ramp and off-ramp. S0 merely has an off-ramp as the lower node, with the upper boundary of the freeway corridor as its upper node. While S(N-1) merely has an on-ramp as the upper node, with the lower boundary of the freeway corridor as its lower node. Variables used in this paper are defined below:

$q_0(k)$: the number of vehicles entering the freeway corridor from upper section of S0 during interval k;
$q_i(k)$: the number of vehicles entering the freeway corridor from on-ramp i during interval k, $i = 1, 2, \dots, N-1$;
$y_j(k)$: the number of vehicles leaving the freeway corridor from off-ramp j during interval k, $j = 1, 2, \dots, N-1$;
$y_N(k)$: the number of vehicles leaving the freeway corridor from lower section of S(N-1) during interval k;
$T_{ij}(k)$: the number of vehicles entering the freeway corridor from on-ramp i during interval k with destination at off-ramp j, i.e. the time-varying O-D flows, where $0 \le i < j \le N$;
$b_{ij}(k)$: split parameter, it equals to the ratio of vehicles in $q_i(k)$ which leave freeway corridors from off-ramp j;
$U_i(k)$: the number of vehicles passing upper section of segment i during interval k, $i = 0, 1, ..., N-1$.

Figure 1 shows that, since there is only one single route between any two nodes, after entering the freeway corridor from an on-ramp or the upper boundary, vehicles can only travel along the mainline to leave the freeway from an off-ramp or the lower boundary. Meanwhile, the upper boundary traffic counts $q_0(k)$, lower boundary counts $y_N(k)$, on-ramp counts $q_i(k)$ and off-ramp counts $y_j(k)$, as trip generation and attraction of each node, could be obtained by detectors, as well as the mainline traffic counts $U_i(k)$. Therefore, the problem to be solved can be stated as: how to get the time-varying O-D flows $T_{ij}(k)$ or split parameters

$b_{ij}(k)$ from the time-series of known traffic counts.

As most other models, there exist the following relations:

$$q_i(k) = \sum_{j=i+1}^{N} T_{ij}(k) \qquad i = 0,1,...,N-1 \tag{1}$$

$$T_{ij}(k) = q_i(k) b_{ij}(k) \qquad 0 \le i < j \le N \tag{2}$$

$$0 \le b_{ij}(k) \le 1 \qquad 0 \le i < j \le N \tag{3}$$

$$\sum_{j=i+1}^{N} b_{ij}(k) = 1 \qquad i = 0,1,...,N-1 \tag{4}$$

Moreover, since there are some distances between any pair of nodes in the freeway corridor, travel time of vehicles between each O-D pair could not be neglected, and the influence of travel time should be taken into account in the model. Assume that after entering the freeway corridor from an on-ramp or the upper boundary, vehicles travel at a speed with a certain range, enter the next lower section orderly, and finally leave the freeway from an off-ramp or the lower boundary. The variable $\rho_{ij}^m(k)$ is introduced to denote the proportion of O-D flows $q_i(k-m)b_{ij}(k-m)$ in interval $(k-m)$ that arrive at an off-ramp during interval k, namely, the contribution of $q_i(k-m)b_{ij}(k-m)$ to $y_j(k)$. $\rho_{ij}^m(k)$ is named influence factor of travel time in this paper. Therefore, the relation between entry traffic volume, split parameter and exit traffic volume can be stated as:

$$y_j(k) = \sum_{m=0}^{M} \sum_{i=1}^{j-1} \rho_{ij}^m(k) q_i(k-m) b_{ij}(k-m) \tag{5}$$

where M is the maximum number of intervals during which trip generation at upper node i has influence on trip attraction at lower node j, which is set to be the number of intervals corresponding to the maximum travel time for vehicles to traverse the freeway corridor.

Obviously, there exist the following natural constraints of $\rho_{ij}^m(k)$:

$$0 \le \rho_{ij}^m(k) \le 1, \quad 0 \le i < j \le N, \quad m = 0,1,...,M \tag{6}$$

$$\sum_{m=0}^{M} \rho_{ij}^m(k+m) = 1, \; 0 \le i < j \le N \tag{7}$$

For mainline traffic counts, based on the similar method, the dynamic relation can be represented as:

$$U_l(k) = \sum_{m=0}^{M} \sum_{i=0}^{l-1} \rho_{il}^m(k) \left[\sum_{j=l+1}^{N} T_{ij}(k-m) \right] + q_l(k) \tag{8}$$

In another form, it can be expressed as:

$$U_l(k) - q_l(k) = \sum_{m=0}^{M} \sum_{i=0}^{l-1} \sum_{j=l+1}^{N} q_i(k-m)\rho_{il}^m(k) b_{ij}(k-m), \qquad l = 1,2,...,N-1 \tag{9}$$

In summary, equations (8) and (9) formulated the dynamic interrelations between time-varying O-D flows and link traffic counts.

3. TIME-VARYING TRAVEL TIME ESTIMATION

Since $\rho_{ij}^m(k)$ in above equations have deep relation with time-varying travel time, we turn to the estimation method of dynamic route travel time in this section.

Concerning with freeway corridors, the average travel time $\tau_a(k)$ of vehicles on a sub-corridor a in interval k can be represented as the sum of following two items: 1) free travel time D_{a1} on sub-corridor a; 2) delay time $D_{a2}(k)$ related with traffic volume, which is in the following equation:

$$\tau_a(k) = D_{a1} + D_{a2}(k) \tag{10}$$

D_{a1} can be calculated from equation (11), where l_a is the length of sub-corridor a, ω_{a0} is the free flow speed on sub-corridor a.

$$D_{a1} = l_a / \omega_{a0} \tag{11}$$

Delay item $D_{a2}(k)$ is determined by traffic status in front when vehicles enter sub-corridor a. For a brief case, the decisive factor is assumed to be the average traffic flow density $e_a(k)$. Further define $x_a(k)$ as number of vehicles in sub-corridor a at beginning time of interval k, $u_a(k)$ as average traffic volume entering sub-corridor a during interval k, $v_a(k)$ as average traffic volume leaving sub-corridor a during interval k, and Δk as time length of one unit interval. Then we get:

$$e_a(k) = \frac{[u_a(k) - v_a(k)]\Delta k / 2 + x_a(k)}{l_a} \tag{12}$$

Therefore,

$$D_{a2}(k) = \alpha [e_a(k)]^{\beta} \tag{13}$$

where parameter α is a real number, β is an integer, and they can be calibrated by using practical data.

After link travel time $\tau_a(k)$ is got from equations (11), (12) and (13), the route travel time during each interval can be obtained by recursive method. Assume that the freeway corridor is composed of node $r = 1,2,\ldots,i,\ldots,$ $\eta^{ij}(k)$ is the average travel time for entering vehicles from on-ramp i in interval k to arrive at off-ramp j, $\tau_a(k)$ is the average travel time for entering vehicles of sub-corridor $a=(j-1,j)$ during interval k. Under the condition that $\eta^{i(j-1)}(k)$ is an integer times of Δk, one can get:

$$\eta^{ij}(k)=\eta^{i(j-1)}(k)+\tau_a[k+\frac{\eta^{i(j-1)}(k)}{\Delta k}], \quad 0\le i<j\le N \tag{14}$$

In case that $\eta^{i(j-1)}(k)$ is not an integer times of Δk, its adjacent two integers can be used for approximation. Define $\mathrm{INT}()$ as an integer conversion function, so $\mathrm{INT}(x)$ denotes the maximum integer not larger than x. Further define $\xi^{i(j-1)}(k)=\mathrm{INT}[\eta^{i(j-1)}(k)/\Delta k]$, equation (14) can be transformed into the following one:

$$\eta^{ij}(k)=\eta^{i(j-1)}(k)+\frac{\tau_a[k+\xi^{i(j-1)}(k)]+\tau_a[k+\xi^{i(j-1)}(k)+1]}{2}, \quad 0\le i<j\le N \tag{15}$$

From esquation (15), we can get the time-varying route travel between each pair of nodes.

4. REVISED MODELS

Though dynamic travel time can be got through equation (15), $\rho_{ij}^{m}(k)$ is still unknown. Here we analyzed this problem in two scenarios: 1) Assume that $\rho_{ij}^{m}(k)$ is known, and it can be calculated by route travel time under some assumptions; 2) Take $\rho_{ij}^{m}(k)$ as unknown variables. These two types of models are shown as following respectively.

4.1 Scenario 1: Influence Factor of Travel Time is Known

In this scenario, the travel time can be got from test vehicles, or from historical data directly. Since travel time is already known, the relationship $\rho_{ij}^{m}(k)$ between route traffic counts, namely, O-D flows for freeway corridors, and link traffic measurements can be calculated from travel time under certain assumption.

Well then, denote $\eta^{ij}(k)$ as the average travel time for O-D flows $q_i(k)b_{ij}(k)$ entering freeway corridors from on-ramp i during interval k to arrive at off-ramp j. Generally speaking, vehicles in $q_i(k)b_{ij}(k)$ have similar behavioral characteristics. Therefore, if $\eta^{ij}(k)$ is rather big, travel times of these vehicles can be assumed to obey normal distribution with mean value of $\eta^{ij}(k)$, and other parameters can be determined by corresponding historical data.

In case that $l\Delta k\le k\Delta k+\eta^{ij}(k)<(l+1)\Delta k$, contributions of O-D flows $q_i(k)b_{ij}(k)$ to $y_j(l-b)$, …, $y_j(l-1)$, $y_j(l)$, $y_j(l+1)$, …, $y_j(l+b)$ can be calculated approximately, thus we can get $\rho_{ij}^{l-b-k}(l-b)$, …, $\rho_{ij}^{l-1-k}(l-1)$, $\rho_{ij}^{l-k}(l)$, $\rho_{ij}^{l+1-k}(l+1)$, …, $\rho_{ij}^{l+b-k}(l+b)$, where b presents the number of influence intervals depending on complexity of the problem.

Further more, since the number of unknown variables is much more than measured traffic counts, the problem is underdetermined. In order to tackle it, first we assume that split parameters keep constant during consecutive K intervals, then track the dynamic characteristics of $b_{ij}(k)$ by rolling horizon method (Bell, 1991). For convenience of description, we again adopt the common upper bound M in the model formulation, in other words, estimate an average $b_{ij}(k)$ for recent M intervals.

Consequently, we replace all $b_{ij}(k-m)$ with $b_{ij}(k)$, and get the model formulation. To minimize the influence of input errors on the outputs, we adopted the form of absolute values of errors.

$$\begin{aligned} J = \min \sum_{k=1}^{M}\sum_{j=1}^{N} | y_j(k) - \sum_{m=0}^{M}\sum_{i=0}^{j-1} \rho_{ij}^{m}(k) q_i(k-m) b_{ij}(k) | \\ + \min \sum_{k=1}^{M}\sum_{s=1}^{N-1} | U_s(k) - q_s(k) - \sum_{m=0}^{M}\sum_{i=0}^{s-1}\sum_{j=s+1}^{N} q_i(k-m)\rho_{is}^{m}(k) b_{ij}(k) | \end{aligned} \tag{16a}$$

$$\text{s.t.} \quad \sum_{j=i+1}^{N} b_{ij} = 1, \;\; b_{ij} \geq 0, \quad 0 \leq i < j \leq N \tag{16b}$$

$$b_{ij}(k) = b_{ij}(l), k = l+1, l+2, \ldots, l+M \tag{16c}$$

$$0 \leq \rho_{ij}^{m}(k) \leq 1, \quad 0 \leq i < j \leq N, \quad m = 0,1,\ldots,M \tag{16d}$$

$$\sum_{m=0}^{M} \rho_{ij}^{m}(k+m) = 1, \quad 0 \leq i < j \leq N \tag{16e}$$

4.2 Scenario 2: Influence Factor of Travel Time is Unknown

In this scenario, since the objective function is to minimize the sum of absolute differences between observed and estimated exit traffic counts at off-ramps and the lower boundary of the freeway, the arrival time, rather than the departure time, should be unified in the estimation of travel time. Equation (15) can be easily transformed from a forward recursion to a backward recursion. Hence, we can still get the average travel time between each pair of nodes in the freeway.

Since $\rho_{ij}^{m}(k)$ is unknown, it is noticeable that there are a large number of unknown parameters in the system equations (5) and (9), and the dynamic constraints of equations (4) and (7). The number of these variables increases fast with M. Therefore, further information and simplification are necessary to make the model overdetermined and sufficiently efficient.

From a macroscopic perspective, we assume that the speed of entering vehicles during the same time interval may be distributed in a small range. Further denote:

$$\eta_{ij}^{-}(k) = \mathrm{INT}[\eta^{ij}(k)/\Delta k], \qquad \eta_{ij}^{+}(k) = \eta_{ij}^{-}(k) + 1 \tag{17}$$

Therefore, we can get the conclusion that most vehicles that arrive at node j during interval k depart from node i within intervals $k-\eta_{ij}^{-}(k)$ and $k-\eta_{ij}^{+}(k)$. Equations (16) can thus be simplified as:

$$\begin{aligned} J = \min\{ & \sum_{k=1}^{M}\sum_{j=1}^{N} | y_j(k) - \sum_{i=0}^{j-1}[\rho_{ij}^{+}(k)q_i(k-\eta_{ij}^{+}(k)) + \rho_{ij}^{-}(k)q_i(k-\eta_{ij}^{-}(k))]b_{ij}(k)| \\ & + \sum_{k=1}^{M}\sum_{s=1}^{N-1} | U_s(k) - q_s(k) - \sum_{i=0}^{s-1}\sum_{j=s+1}^{N}[\rho_{is}^{+}(k)q_i(k-\eta_{is}^{+}(k)) + \rho_{is}^{-}(k)q_i(k-\eta_{is}^{-}(k))]b_{ij}(k)|\} \end{aligned} \tag{18a}$$

$$\text{s.t.} \quad \sum_{j=i+1}^{N} b_{ij}(k) = 1, \ \ b_{ij}(k) \ge 0, \quad 0 \le i < j \ge N \tag{18b}$$

$$b_{ij}(k) = b_{ij}(l), k = l+1, l+2, \dots, l+M \tag{18c}$$

$$\rho_{ij}^{+}(k) = \rho_{ij}^{\eta_{ij}^{+}(k)}(k), \ \ \rho_{ij}^{-}(k) = \rho_{ij}^{\eta_{ij}^{-}(k)}(k), \ \ 0 \le i < j \le N \tag{18d}$$

$$0 \le \rho_{ij}^{+}(k), \rho_{ij}^{-}(k) \le 1, \quad 0 \le i < j \le N \tag{18e}$$

$$\rho_{ij}^{+}(k) + \rho_{ij}^{-}(k) = 1, \quad 0 \le i < j \le N \tag{18f}$$

Equation (18) formulates the revised parameter optimization model for dynamic O-D flows estimation in freeway corridors. Different from equation (16), $\rho_{ij}^{+}(k)$ and $\rho_{ij}^{-}(k)$ are unknown here.

5. GENETIC ALGORITHM FOR ESTIMATION PROBLEM

Different from least square problems, the objective function of these two revised models are both a sum of absolute values, and there is no simple optimization algorithm to solve them. Meanwhile, the models have following characteristics: 1) The objective function is in the form of simple errors. Transformed into standard fitness function, the upper boundary of original objective function can be ascertained according to accuracy request; 2) Using appropriate coding methods, the constraints of split parameters can be satisfied automatically. Therefore, here we put forward a genetic algorithm to solve the second model, and the first one is easier to be tackled. Flow chat of this algorithm is shown in Figure 2.

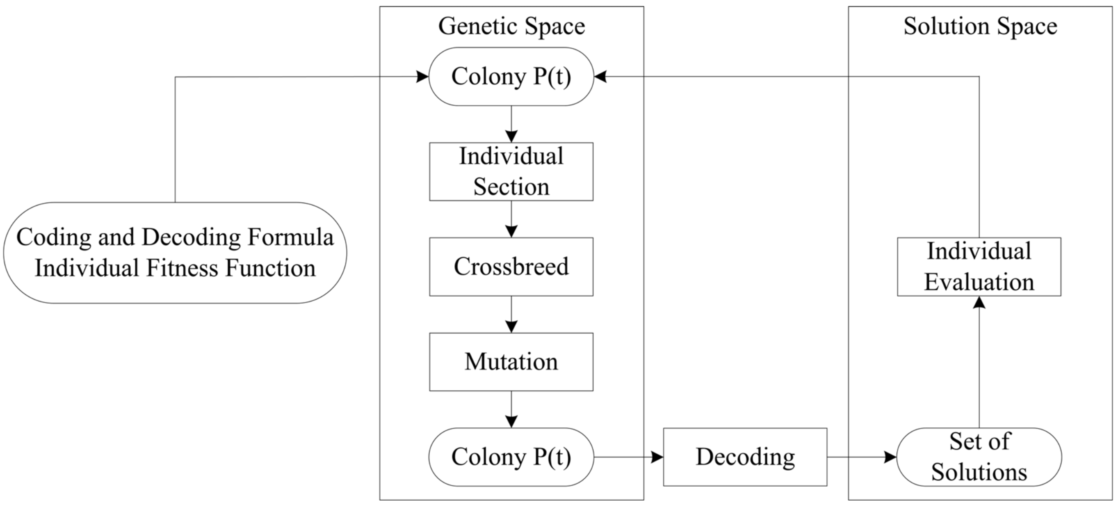

Figure 2. Flow Chart of Genetic Algorithm

There are several key issues in genetic algorithm illuminated as follows.

5.1 Coding and Decoding Methods

Use binary encoding method (Zhou and Sun, 1999), and the solution space of original problem is mapped to bit space $B^l = \{0,1\}^l$, then carry out genetic process within B^l, and convert the results to their actual value through decoding process and evaluate their fitness.

The mapping process from solution space to $B^l = \{0,1\}^l$ is as following: Suppose an unknown variable needs a binary code with N bits, since the code denotes 2^N numbers from 0 to $(2^N - 1)$, the definition field of the unknown variable is divided into $(2^N - 1)$ regions with equal length, and there are 2^N different points including the two endpoints. From point 0 to point 1, each point corresponds to a binary code from $\underbrace{00\ldots0}_{N}$ to $\underbrace{11\ldots1}_{N}$, so the accuracy of this coding method is $(2^N - 1)^{-1}$. Therefore we can get N according to the accuracy request of the problem.

5.2 Individual Fitness Function

Use fitness function to transform objective function value J to individual fitness $F(X)$.

$$\begin{aligned} F(X) &= C_{\max} - J(b), \qquad && \text{if} \quad J(b) < C_{\max} \\ &= 0. && \text{if} \quad J(b) \geq C_{\max} \end{aligned} \tag{19}$$

Here $C_{\max}$ is the upper bound of original fitness function, and is set to be 1000 in this paper.

5.3 Selection Strategy

Use the roulette wheel selection method based on the fitness percentage (Zhou and Sun, 1999), and the process is described below:

1) Accumulate each individual's fitness by step, obtain the sum value S_i, until the final sum value S_n, here n is the number of individuals;
2) Generate averagely distributed random number R in the range of $[0, S_n]$;
3) Compare each S_i with R orderly, the first individual i with corresponding S_i not less than R is selected as the replicated object;
4) Repeat step 2 and step 3 until satisfying requisite number of individuals.

The selection method is quite similar to the roulette in gambling, the greater the area of fan sector, the larger probability that dice would fall into it. That is to say, the bigger the individual fitness, the more chance that it would be selected, and the more likely its genetic structure is to be inherited by the next generation. Obviously, although the probability that individuals with small fitness are to be replicated is small, they may be replicated exceptionally, which leads to the variability of individuals.

5.4 Controlling Parameters

Controlling parameters mainly include the scale of colony (80 in this paper), maximum time of algorithm execution (200), and probability of executing different genetic operation (crossbreed probability is 0.6, and mutation probability is 0.04). All these parameters are based upon the requisite accuracy and efficiency of genetic algorithm.

5.5 Genetic Operators

Use one-dot method for crossbreed operation. One-dot crossbreed method is to choose a crossbreed point randomly from two father codes, then exchange sub-codes of them. For instance, two father codes are $\theta_1 = (10110101)$ and $\theta_2 = (01011001)$ respectively, and the random crossbreed point is 5. Thus one should exchange sub-codes (101) and (001) of θ_1 and θ_2 to obtain two new codes: $\theta_1' = (10110001)$ and $\theta_2' = (01011101)$.
Mutation operators in binary coding method are quite simple, which merely reverse individual bit at certain probability p_m, that is, the opposition of 1 is 0; while the opposition of 0 is 1.

5.6 Terminating Principle for Genetic Algorithm

Since genetic algorithm does not make use of information such as grads, individual's position in solution space can not be ensured during genetic process, thus traditional methods could not determine whether the algorithm is convergent. This paper pre-set the iterative time as 200 to terminate the algorithm.

With above illumination, the genetic algorithm can be realized in computer program. Since constraints (18b) and (18e) may not be satisfied, we employ the truncation and normalization process proposed by Nihan and Davis (1987) to solve it.

6. SIMULATION EXAMPLE

To testify the veracity and efficiency of the model and algorithm, this section illustrate their applications and effectiveness through simulation experiments. Generally, here we use the model in scenario 2, i.e. influence factors of travel time are unknown, and design following three types of experiments.

1) Basic characteristics: When split parameters keep constant in K intervals, investigate the status that estimated value approaches to actual value with the increase of genetic times;
2) Characteristics with fluctuation in input data: When input data fluctuate within some error range, investigate its influence to the estimated value;
3) Characteristics of tracking dynamic split parameters: Use rolling horizon method to track the dynamic characteristics of split parameters, and compare them with Chang and Wu (1994) to see its improvements.

6.1 Network Design and Data Generation

A simple freeway corridor shown in Figure 3 was used for numerical analysis. This corridor contains one upper boundary, on on-ramp, two off-ramps, and one lower boundary. The geometric characteristics are show as following:

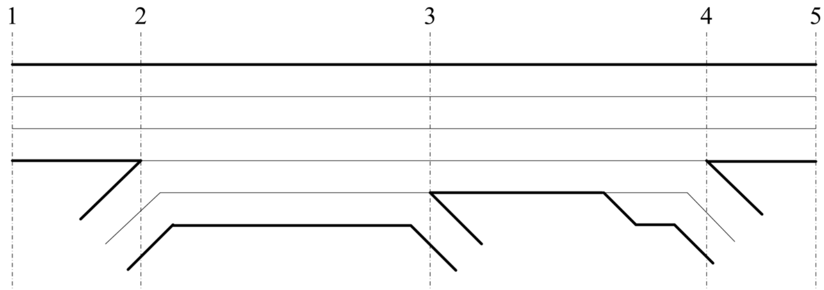

Figure 3. Freeway Corridor for Simulation Example

Segment 1-2: 2404 meters, 3 lanes;
Segment 2-3: 4402 meters, 5 lanes, with an off-ramp of 1 lane;
Segment 3-4: 4266 meters, 4 lanes, with an off-ramp of 2 lanes;
Segment 4-5: 1727 meters, 3 lanes.

According to the geometric characteristics, obviously there are six O-D pairs to be estimated. The time-varying split parameters are denoted as:

$$b_{13}(k),\ b_{14}(k),\ b_{15}(k),\ b_{23}(k),\ b_{24}(k),\ b_{25}(k).$$

Since CORSIM (ITT Industries, 2001) can take dynamic O-D matrices in 19 time intervals as input data for freeway corridors, the randomly generated time-series of O-D percentages as shown in Table 1 were simulated with it to produce the time-varying link traffic counts. In this example, the free flow speed was set as 100 km/h, the unit time interval was set as 1.5 minutes, and some parameters, such as α and β in equation (13), could be calibrated from CORSIM output file.

Table 1. The Input Time-Varying Split Parameters

Interval	$b_{13}(k)$	$b_{14}(k)$	$b_{15}(k)$	$b_{23}(k)$	$b_{24}(k)$	$b_{25}(k)$
1	0.183	0.323	0.493	0.200	0.320	0.480
2	0.174	0.327	0.499	0.190	0.324	0.486
3	0.165	0.322	0.513	0.180	0.320	0.500
4	0.146	0.329	0.525	0.160	0.328	0.512
5	0.137	0.333	0.530	0.150	0.331	0.519
6	0.140	0.321	0.533	0.160	0.319	0.521
7	0.155	0.309	0.536	0.170	0.307	0.523
8	0.165	0.305	0.530	0.180	0.303	0.517
9	0.174	0.302	0.524	0.190	0.300	0.510
10	0.183	0.291	0.526	0.200	0.288	0.512
11	0.193	0.295	0.512	0.210	0.292	0.498
12	0.202	0.292	0.506	0.220	0.289	0.491
13	0.212	0.296	0.492	0.230	0.293	0.477
14	0.221	0.293	0.486	0.240	0.289	0.471
15	0.231	0.297	0.473	0.250	0.292	0.458
16	0.221	0.293	0.486	0.240	0.289	0.471
17	0.212	0.304	0.484	0.230	0.300	0.470
18	0.193	0.311	0.496	0.210	0.308	0.482
19	0.183	0.323	0.493	0.200	0.320	0.480

We also adopted input data with larger variations, and satisfactory results were achieved. To compare with Chang and Wu (1994) more fairly, we adopted the input data shown in Table 1. Furthermore, though the initial values in genetic algorithm can be taken optionally, the following set of initial split parameters was used for the estimation, and the results were compared with Chang and Wu (1994) with the same initial values in Kalman filtering process:

$$b_{13} = 0.33,\ \ b_{14} = 0.33,\ \ b_{15} = 0.34,\ \ b_{23} = 0.33,\ \ b_{24} = 0.33,\ \ b_{25} = 0.34\,.$$

6.2 Experimental Results

Due to the limitation of paper length, we make use of $b_{13}(k)$ and $b_{25}(k)$ to analyze the results.

6.2.1 Basic Characteristics

Set the maximum iterative times during one time interval as 200. Under the condition that K equals to 5, i.e. O-D fractions keep constant during recent 5 intervals, the characteristics that split parameters $b_{13}(1)$ and $b_{25}(1)$ approach actual values with increase of iterative times are shown in Figure 4.

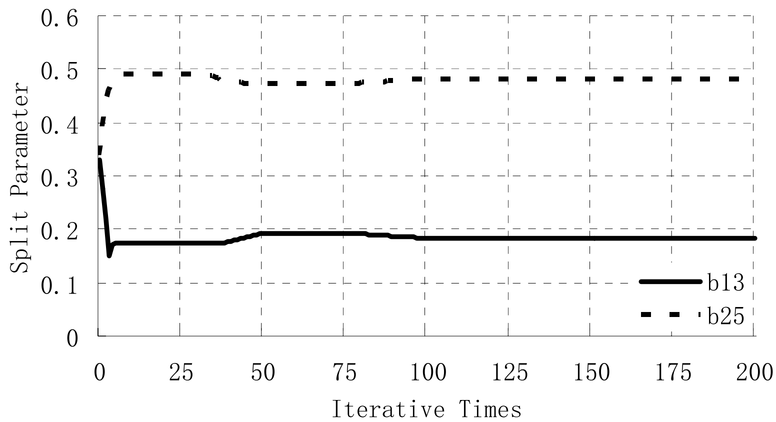

Figure 4. Basic Characteristics

From the above figure, one can see that after about 100 times of iteration, estimated results have already kept steady, and almost the same as actual values. Also we found that since importing time-series of traffic counts from original data file, till finding out optimal individual according to objective function within all individuals of each generation and writing it into output file (about 1.6 MB), the CPU time is only 3.4 seconds. Therefore, the model and algorithm are rather accurate and efficient.

6.2.2 Characteristics with Fluctuation in Input Data

Since there might be some errors in measured link traffic counts, random generator is used to engender certain errors in exit flows $y_j(k)$, while other link counts and actual value of split parameters keep invariable.

Under the condition that fluctuations are within the range of $\pm 5\%$, the characteristics that split parameters $b_{13}(1)$ and $b_{25}(1)$ approach actual values with increase of iterative times are shown in Figure 5. Here the number of intervals during which split parameters are assumed constant, in other words, K, is still 5.

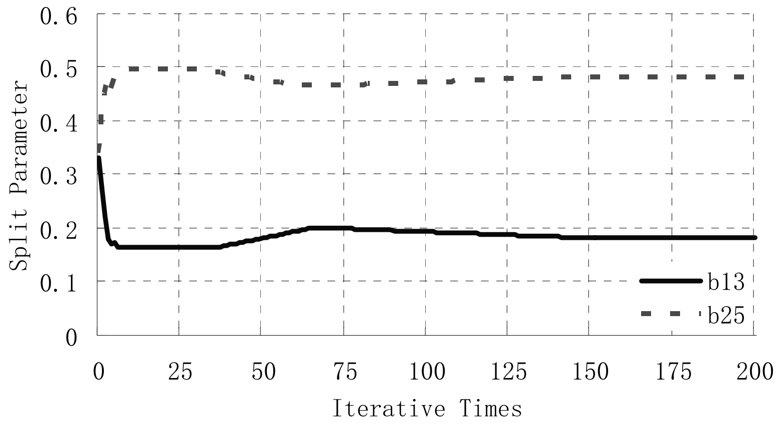

Figure 5. Characteristics with Fluctuation in Input Data

Comparing with Figure 4, one can find that the error at the beginning stage of iteration becomes bigger, and the speed of convergence becomes slower. However, after about 150 times of iteration, the estimated results also remain steady, and almost the same as actual values. Therefore, the model and algorithm still keep accurate and efficient when there exist some errors in the input data, and are rather robust.

6.2.3 Characteristics of Tracking Dynamic Split Parameters

Using rolling time horizon, we can track the dynamic characteristics of split parameters. With the given initial value, the estimation process was executed using both the model presented in this article (named GA) and Chang and Wu (1994) (named KF). The Root Mean Square Error (RMS) and Root Mean Square Error Normalized (RMSN) between the estimated and actual values are selected as the evaluation criteria, as shown in equations (20), where $\tilde{b}_{ij}(k)$ is estimated value, and $b_{ij}(k)$ is actual value. The statistical results of RMS and RMSN and the relative improvements are shown in Table 2. Because the estimation results of Kalman filtering (Chang and Wu, 1994; Chui and Chen, 1991) during its initialization period are usually unreliable, the results of the first five intervals were excluded from the statistics.

$$RMS = \sqrt{\sum_{k=1}^{n} (b_{ij}(k) - \tilde{b}_{ij}(k))^2 / n}\,, \quad RMSN = \sqrt{n \cdot \sum_{k=1}^{n} (b_{ij}(k) - \tilde{b}_{ij}(k))^2} \Bigg/ \sum_{k=1}^{n} b_{ij}(k) \times 100\% \qquad (20)$$

From equations (20), one can find that the relative improvements for RMS and RMSN should be the same, which also can be seen from Table 2.

The estimation results of b_{13} and b_{25} using both two methods are shown in Figure 6 and Figure 7 respectively. From Table 2 and Figure 6, Figure 7, one can find out that the proposed model and algorithm yield substantial improvements in both accuracy and stability in the estimation process compared with KF algorithm. The model and algorithm presented in this article on average reduce the RMS and RMSN of the time-varying split parameters by about 32%. Moreover, during beginning intervals, the estimation results of GA are much more accurate than KF, since KF algorithm needs some intervals to finish its initialization.

Table 2. Statistical Results of RMS and RMSN

Split Parameters	RMS			RMSN		
	KF	GA	Relative Improvement	KF	GA	Relative Improvement
b_{13}	0.021	0.012	39.41%	10.72%	6.50%	39.41%
b_{14}	0.027	0.014	47.90%	8.87%	4.62%	47.90%
b_{15}	0.025	0.015	38.01%	4.93%	3.06%	38.01%
b_{23}	0.025	0.023	8.34%	12.11%	11.10%	8.34%
b_{24}	0.026	0.015	39.36%	8.53%	5.17%	39.36%
b_{25}	0.030	0.023	23.70%	6.05%	4.62%	23.70%
Average	0.025	0.017	32.46%	8.54%	5.84%	32.46%

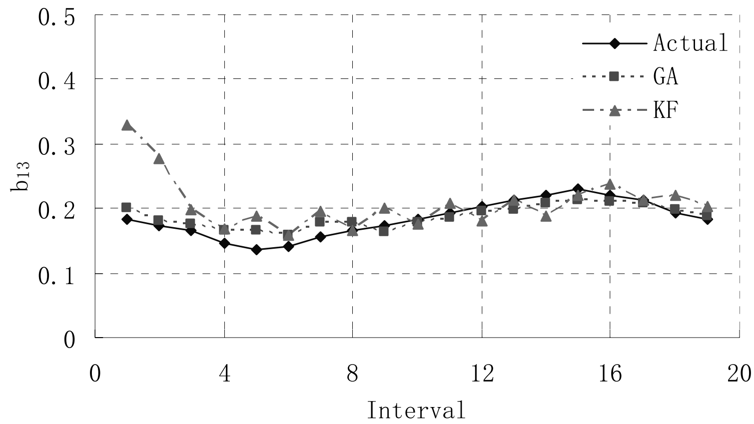

Figure 6. Estimation Results of b_{13}

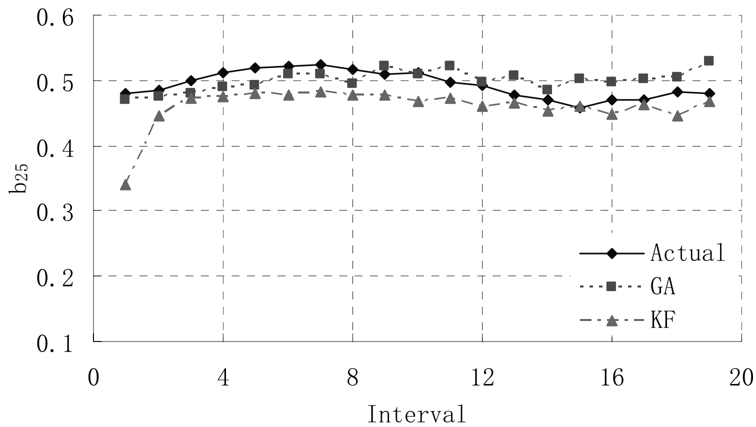

Figure 7. Estimation Results of b_{25}

On the other hand, the CPU time of GA is 3.4 seconds, while KF needs only 0.57 seconds. The reason is that GA is iterative, while KF is recursive, which is more efficient. However, the efficiency of GA is enough for practical use.

7. CONCLUSIONS AND FURTHER RESEARCH

In this paper, a parameter optimization model has been formulated for estimating dynamic O-D flows from time-series of link traffic counts in freeway corridors. Based on a comprehensive review of existing methods, a recursive estimation method of time-varying travel time is proposed, a nonlinear dynamic interrelation between time-dependent O-D flows and traffic flow measurements is presented, which captures the effect of travel time variability. Two categories of revised models are put forward, along with the corresponding genetic algorithm and its six key issues. The reported simulation example has demonstrated the accuracy, robustness and efficiency of the proposed model and algorithm.

Further research should be directed towards three aspects. The first is to extend the model and algorithm to a real-size network. The second is to take into account traveler information provided by ATIS. And the third, to integrate the dynamic estimation methods with ATMS, such as traffic signal control and route guidance systems.

ACKNOWLEDGEMENTS

The research herein reported has been supported by Beijing Municipal Science and Technology Commission project (H030630530120) partially. The authors would like to thank the engineers for attending this project and the anonymous referees for the careful review of this paper.

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